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**EEG SUB-BAND FREQUENCY  
ANALYSIS OF SPECTROGRAM  
IMAGE FOR BALANCED BRAINWAVE  
AND IQ APPLICATIONS**

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of the requirements for the degree of  
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## ABSTRACT

This thesis introduces new methods in analyzing Electroencephalogram (EEG) signal by utilizing EEG spectrogram image and image processing texture analysis called Gray-level Co-occurrence Matrices (GLCM). The methods attempt to apply in balanced brain and Intelligence Quotient (IQ) applications. The relationship between balanced brain and IQ application also proposed in this thesis. Collection of EEG signals were recorded from 101 volunteers. EEG signals recorded for the balanced brain application contain closed eyes state meanwhile for the IQ application contains closed eyes and opened eyes state. Before processing the information from the EEG signals, signal preprocessing is done to remove artefacts and unwanted signal frequencies. A time-frequency based technique called EEG spectrogram image was used to generate an image from EEG signal. The spectrogram image was produced for each EEG signals sub-band frequency Delta, Theta, Alpha and Beta. The GLCM texture analysis derives features from EEG spectrogram image. Then, Principal Component Analysis (PCA) was applied to reduce the results and selected principal components features were used as inputs to the classifier. Two classifiers involved in this experiment are K-Nearest Neighbor (KNN) and Artificial Neural Network (ANN). The number of training and testing ratio is assessed at 70 to 30 and 80 to 20 to find the best model based on percentage of accuracy, sensitivity, specificity as well as Mean Squared Error (MSE). The relationship pattern of balanced brain and IQ application were observed via histogram and then Scatterplot. The strength and significant of the relationship was evaluated by using Pearson correlation test. The percentage of correctness classification for balanced brain application is 90% and MSE 0.1. The sensitivity and specificity of this application is ranging from 66.67% to 100%. The accuracy for IQ application is 94.44% and MSE 0.0752. Meanwhile, the sensitivity and specificity of this application is ranging from 0% to 100%. The relationship between balanced brain and IQ achieved with positive and strong correlation with  $r$  ranging between 0.860 to 1.000 and  $p < 0.05$  for some cases. The experiments reported in this thesis showed that the proposed technique were highly successful in indexing the balanced brain level and IQ.

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## LIST OF ABBREVIATIONS

### Abbreviations

EEG	Electroencephalogram
IQ	Intelligent Quotient
PSD	Power Spectrum Density
ESD	Energy Spectrum Density
TF	Time-frequency
ECG	Electrocardiogram
GLCM	Gray-level Co-occurrence Matrices
KNN	K-Nearest Neighbor
ANN	Artificial Neural Network
BCI	Brain Computer Interfacing
BMI	Brain Machine Interfacing
STFT	Short Time Fourier Transform
PCA	Principal Component Analysis
MEG	Magnetoencephalogram
GSR	Galvanic skin response
EOG	Electrooptigram
WAIS	Wechsler Adult Intelligence Scale
FD	Fractal Dimension
EMG	Electromyogram
ICA	Independent Component Analysis
BSS	Blind Source Separation
MLP	Multilayer Perceptron
FIR	Finite Impulse Response
FFT	Fast Fourier Transform
LMS	Least-mean-square
SNR	Signal-to-noise Ratio
MCD	Mild Cognitive Disturbances
LDA	Linear Discriminant Analysis

SVM	Support Vector Machine
RBF	Radial Basis Function Network
RMSE	Root Mean Squared Error
MSE	Mean Squared Error
SSE	Sum of Squared Error
KS	Kolmogorov-Smirnov
SW	Shapiro-Wilk
FT	Fourier Transform
ERP	Event Related Potentials
AR	Alpha Ratio
BR	Beta Ratio
PDF	Probability Density Function

# **CHAPTER ONE**

## **INTRODUCTION**

### **1.1 BACKGROUND**

Biomedical engineering is a field of study where principles of engineering design and problem solving skills are applied to biological and medical sciences, which consequently have helped improve healthcare diagnosis, monitoring and therapy. There have been numerous studies in the field that have resulted in the fabrication and production of electronics devices that assist medical practitioners in diagnosing the health of their patients. One such device is the Electroencephalogram (EEG) which is used to analyse the human brain. The device captures brainwaves in the form of electric signals which are generated from the activities of neurons in the brain. The brainwaves, usually classified into four frequency bands called Delta, Theta, Alpha and Beta signals, are widely used for diagnosis of epilepsy, tumor and Alzheimer [1-3], while some studies have used brainwaves for determining the levels of balanced brain [4, 5] and Intelligence Quotient (IQ) [6, 7] applications. In this thesis, EEG signals from the brainwaves is used to determine the levels of balanced brain and IQ in a human being. The research on balanced brain is inspired from the studies of brain dominance between the left and right hemispheres of the brain. In a high balanced brain situation, both the left and right hemispheres of the brain are optimally used; on the contrary, in a low balanced brain situation, one uses more of the left hemisphere of the brain, or vice-versa. Additionally, the studies on IQ is focused on areas of Mathematics and logic; high IQ means good knowledge and understanding in Mathematics and logic, and, on the contrary, low IQ means less knowledge and understanding in Mathematics and logic.

The original EEG signal, which is in time-domain, have to be converted into frequency-domain before it can be analysed according to the Delta, Theta, Alpha and Beta frequency bands; the signals that lie outside the range of the four frequency bands is called noise or artefact. In some studies, all four frequency bands are utilised in the analysis, such as in the experiment conducted to analyse the development of the right

hemisphere of the brain of infants [4]; however, in other studies, only certain frequency bands are used, such as the use of Alpha and Theta frequency bands in the analysis of the levels of IQ in children and adults [6].

EEG signals are usually processed using the conventional signal processing techniques, such as Power Spectral Density (PSD) and Energy Spectral Density (ESD) [8, 9]. The extraction of EEG signals using these techniques have been proven to produce good results. However, it is hypothesized that the signals have other features that can be extracted compared to the features produced from using the conventional techniques. Instead of looking in isolation at the EEG signals either in time-domain or frequency-domain, its rich features can be better observed by combining the two domains, or time-frequency (TF) domain, that produces an image known as spectrogram image. This two-dimensional data has been proven to have strong visualization feature and extensive statistic significance compared to the one-dimensional signal [10]. The use of spectrogram images has been successfully performed in experiments using electrocardiogram (ECG) signals [11], a signal which is similar to EEG signals.

Spectrogram image can be processed using a variety of techniques, and one such technique is the Gray-level Co-occurrence Matrices (GLCM). By extracting the grey values in an image, the technique produces good result when employed to analyse the texture of the image. Even though GLCM is widely used in satellite image applications [12], it is also applied in analysing spectrogram image of ECG signals [11]. Spectrogram image and texture feature analysis using GLCM has been successfully applied to ECG signals, hence, it is envisioned that the same could be done with EEG signals, in spite of the fact that the two signals have different characteristics. The extracted features from the spectrogram image can be classified in accordance with the groups that have been determined by various algorithms. Among the most commonly used algorithms in researches relating to EEG signals are K-Nearest Neighbour (KNN) and Artificial Neural Network (ANN) [13, 14]; both algorithms are supervised algorithms, however, KNN is simpler to implement compared to ANN. KNN uses a distance and k-variable to classify the features of the spectrogram image, while ANN uses parameters such as neurons in hidden layer, learning rate, momentum rate and epoch to classify the features. The purpose of using the algorithms is to investigate the

features of the spectrogram and GLCM in order to characterise EEG signals, however, the two algorithms have different levels of complexity.

Therefore, there is a need for a research to examine the rich features of EEG signals using spectrogram image and GLCM analysis as it is envisaged that the technique would enhance the signal processing technique used in the analysis of EEG signals.

## **1.2 PROBLEM STATEMENT**

Most studies show that EEG signals are analysed in time-domain and frequency-domain. This method has proven to give good results for analysing EEG signals. , EEG signal is non-stationary signal which the frequency varies over time. Therefore, the analysis in time-domain or frequency-domain is ineffective. If the analysis is executed in the frequency domain, the frequency will be analysed but the time is negligible. There is the possibility of another technique to investigate the richness of EEG signals. Thus the combination of time-domain with frequency-domain is a suitable technique to analyse EEG signals. This combination is called spectrogram image. And so, the spectrogram image can be analysed using GLCM texture analysis, which is one of image processing technique. The GLCM is able to characterise the texture of a spectrogram image. The spectrogram image and GLCM may surpass the time-domain and frequency domain analysis in EEG studies. The technique will shows the richness of EEG signals in terms of sub-band for the applications of balanced brain and IQ.

## **1.3 OBJECTIVE**

The aim of the study is to investigate the application of spectrogram image for analysing sub-band frequency of EEG signals, and the proposed technique is to be implemented in determining the levels of balanced brain and IQ. To achieve this aim, the tasks in the research are divided into:

1. Producing the spectrogram image from sub-band frequency of brain waves.
2. Extracting GLCM features from spectrogram image.

3. Classifying the spectrogram image using KNN and ANN and verifying the results of the classification with questionnaires.
4. Correlating the GLCM features of balanced brain with IQ.

#### **1.4 CONTRIBUTIONS**

As a result of the study, three aspects of knowledge that contributes to the field of biomedical engineering are presented in this thesis. The first contribution is that the proposed technique using EEG spectrogram and GLCM texture analysis is to be implemented in balanced brain applications. The second contribution is that the proposed method using EEG spectrogram and GLCM texture analysis is to be implemented in IQ applications. Different conditions are required when collecting data for the two applications; for balanced brain application, data are collected under one state condition - with both eyes closed, while for IQ application, data are collected under two states condition - with both eyes closed and opened. Other than that, data for balanced brain application is verified using brain dominance questionnaire, whereas data for IQ application requires the volunteers to answer the IQ test with their eyes open. The third contribution is to analyse using statistical method and establish the correlation between balanced brain and the IQ. Consequently, it is expected that electronics devices based on the proposed technique is produced which could be used to create a healthier Malaysian society.

#### **1.5 SCOPE OF RESEARCH**

The initial part of the study involved implementing the spectrogram image technique to analyze the sub-band frequency of EEG signals that is applied to balanced brain and IQ applications. The acquisition of EEG signals is conducted at Biomedical Research Laboratory for Human Potential, FKE, Universiti Teknologi MARA (UiTM), Malaysia.

In the study, the number of male and female volunteers is 101 in the age group from 18 to 50 years old. This is the range of adult age is widely used in EEG studies [15-17]. Those who are older than 50 years were not included in the study as their human productivity have decreased [18]. Most of the volunteers are students and staffs

from UiTM. On top of that, the volunteers must be healthy and are not on any medication or prescription drugs that are known to affect EEG reading for at least one month prior to the commencing of the experiment [19-21]. Volunteers who are sick, for example, has fever, cough or cold is not allowed to participate the experiment, but when he or she recovers, they are allowed to participate the experiments.

Since the volunteers are required to respond to the questionnaires and IQ questions, it is essential that the volunteers' vision must be normal or corrected to normal [22]. The volunteers involved in the experiments are different for balanced brain and IQ application. In addition, the data collection are performed in two different sessions. The EEG signals recorded in eyes-closed for balanced brain application, while the EEG signals recorded in eyes-closed and eyes-opened for IQ application.

The GLCM texture analysis is employed to extract the features of the spectrogram of EEG signals and these features is classified using KNN and ANN. The results from the classification exercise are verified with the aid brain dominance questionnaires and IQ questions. Software programming development is carried out using *MATLAB* and *SPSS* is used to conduct statistical analysis on the results.

Finally, the results obtained from KNN and ANN are evaluated and compared in terms of accuracy, MSE, sensitivity and specificity.

## **1.6 THESIS LAYOUT**

This thesis consists of eight chapters. Chapter 1 begins with the background information on brain waves and its importance in the study of balanced brain and IQ applications. Also included in this chapter are the objectives and scopes of the study.

Chapter 2 reviews the literature related to this study. This chapter describes several definitions and information related to the brain, brainwaves, EEG, balanced brainapplication, IQ application, EEG signals in TF domain, image texture analysis and classifiers.

Chapter 3 describes the theories that are applied in this thesis, which cover aspects on EEG signal processing, STFT, GLCM, PCA, KNN and ANN. All calculations and algorithms related to the theories are described in this chapter.

Chapter 4 presents the methodology implemented to conduct the experiments carried out in this study, which cover topics on the utilization of spectrogram image and